Paper:

Novel Human Interface for Game Control Using Voluntarily Generated Biological Signals

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We propose a human interface for video game operation using voluntarily generated biological signals as input. The users choose specific input signals and configure signal measurement based on preferences, physical condition (disabled or not), and degree of disability. Based on input signals, the intended user operations are estimated with a probabilistic neural network (PNN), and then control commands are determined. Our proposed interface enables individuals even with severe physical disabilities to maneuver video games. Experiments confirmed the feasibility of our designed interface by subjects suffering from cervical spine injury.

Keywords: human interface, video game machines, biological signals, probabilistic neural network, pattern discrimination

1. Introduction

Amusement equipments, such as TV games, radio-controlled devices, and entertainment robots being operated using pushbutton switches and joysticks may be difficult to use for physically disabled people, such as amputees. With the annually growing number of physically disabled people in Japan [1], barrier-free environments are necessary for these people to enjoy the same leisure in life as those without disabilities.

As regards the studies on interfaces for the physically disabled, Suzuki et al. [2] developed a large, easy-to-operate pushbutton interface and input manipulated by shifting the user's weight during TV games. Lopes [3] proposed an interface using an input button operated by the extremities. Users without such potential limb use, such as those suffering from cervical spine injury or amyotrophic lateral sclerosis, cannot enjoy such games, however.

Biological signals interpreted from tracings of the electromyogram (EMG) and electroencephalogram (EEG) reflect internal conditions of the human body and intention of body movements. If a movement can be estimated by biological signals, the latter could be substitute for limb use. Other related studies have been done on the control of the external environment and the artificial throat, as well [4, 5].

Implementing biological signals in amusement equipments could enable an interface practical, regardless of the presence of physical disability. In working with such interfaces, Iga et al. [6] developed a computer game, operated by inhalation and exhalation as determined by the breath analysis. Betke [7], Lin et al. [8] used the positioning of the eye as measured by a camera, and Krepki [9] estimated a user's intent from the EEG signals in order to operate a PC pointer for a simple computer game. In the utilization of such equipments, the user should be provided with choices of operation method. Interfaces do not generally adapt to the user's needs, however, and may require considerable training. Also, further development usually targets particular equipment and computer games that do not correspond to ordinary home game machine operation.

In this paper, we propose a human interface using biological signals for the operation of game machines by the seriously disabled. In this system, input of multiple signals is possible, and based on the degree of disability and preference, a signal can be selected and measured. By means of a probabilistic neural network (PNN) [10] to learn and discriminate the measured signal, individual user variations can be adapted and the position of the input signal changed. Moreover, the hardware for controlling the interface and game machines is re-configurable allowing hassle-free addition and alteration of the equipments. A single interface, thus, permits operation of different game machines.

This paper is organized as follows. Section 2 discusses the proposed interface, section 3 explains the prototype developed, section 4 describes the details of the experiments, and section 5 presents the conclusions.

2. Human Interface for Game Control

The human interface we proposed (**Fig.1**) consists of four blocks, which signify the input signal processor, in-

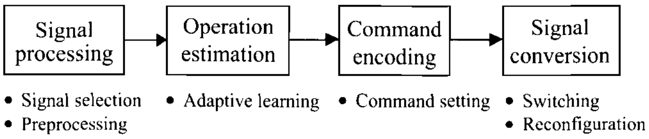


Fig. 1. Concept of the proposed human interface for game control.

tention estimation, command decision, and signal converter. We focus on games in which the user takes time to select operator commands, such as role-playing and table games. The subsections that follow explain the individual components of the interface.

2.1. Input Signal Processor

Biological signals such as EMG signals, exhalation, and acceleration (ACC) signals generated by body movements are measured by appropriate selection of the user's ability. In this study, EMG and joint angle signals were employed, although any biological signal produced by voluntary actions can be used similarly.

Feature extraction against a measured biological signal derives the information for estimating the intended operation. Information interpreted from the biological signal differs with the type of signal and intended operation, so feature extraction is required based on the purpose. The input signal processor conducts feature extraction based on the biological signal and intended operation, and transforms the signal to a feature vector that uses signal characteristics [11]. The biological signal and measuring position acted upon by the user are selected for input to the interface.

2.2. Intention Estimation

After feature extraction, the PNN estimates the intended operation from the biological signals. The PNN, which is a type of statistical pattern recognition based on the Bayesian discrimination theorem, introduces a probability model into a neural network, so posterior probability can be estimated for given input patterns [10]. Because the network discriminates well in pattern recognition, the movement of the user can be recognized from the biological signal as posterior probability of each movement. Through learning, the PNN distinguishes the signal patterns with individual differences and the lag in its measurement, enabling precise pattern recognition. Even when the type of biological signal changes based on the alteration in the user's movement, the pattern can be discriminated well through learning, so that multiple biological signals can be integrated and handled simultaneously.

2.3. Command Decision

Movement of the user k $(k = 1, 2, \ldots, K)$ identified through the intention estimation allocates operator command c_i $(i = 1, 2, \ldots, C)$ of the game machine to the command decision. K denotes the number of movements estimated by the user, and C denotes the command required for operating the game machine. Depending on the game machine, the required total number of C differs. When the number of K exceeds the total number of C, the corresponding estimated movement k with command c_k enables the user to directly execute commands using individual movements. In addition, depending on the user's physical abilities, the number of K precisely calculated by intention estimation may be smaller than C. To operate game machines regardless of disability requires a command decision that executes all commands, even when the number of possible movement is small.

Considering the case when the number of K of movement is smaller than the number of C of command required for operating the equipment, the operator commands are grouped. By changing groups and commands using K movements, the user executes all commands with fewer movements. Explanations below are based on this idea.

When number K of the user's movements and the required number of commands are given, divide all commands into $(K-1)$ groups each $(K \geq 2)$. The number G of the group becomes

$$G = \mathrm{ceil}[C/(K-1)]. \quad \ldots \ldots \ldots \ldots (1)$$

$\mathrm{ceil}[x]$ is a function giving the minimum integer equal to or larger than real number x. The commands included in the group are freely configurable by the user. The user configures the commands in-line, e.g., increasing the number of commands based on the game machine in order to configure the same command for multiple groups. Using the remaining one of K movements allotted to each group, the group is changed.

Based on the above explanation, the user changes groups and selects commands by repeating K movements. When the user executes only one movement $(K = 1)$, the system continues to select commands at predetermined interval T_{td} [s]. The user executes command by conducting the movement when the command is selected. The user thus, executes a required command regardless of the number of K.

2.4. Signal Converter

The operation command is sent to the game machine as a digital signal from the signal converter. Since the communication protocol of the game machine differs with the machine, it must be changed as needed. The signal converter is configured as a field-programmable gate array (FPGA) for easy reconstruction of the circuit. The FPGA, which is a large-scale integrated circuit (LSI), electrically reconfigures the internal circuit by rewriting the program. Less time is spent to develop the transformed signal than through an application-specific integrated circuit (ASIC), allowing redesign of the program. By configuring the signal converter on the FPGA, the circuit is reconfigured as necessary, and it is possible to add and change the game machine.

The signal converter implements a generation of control signal corresponding to the command decision. The

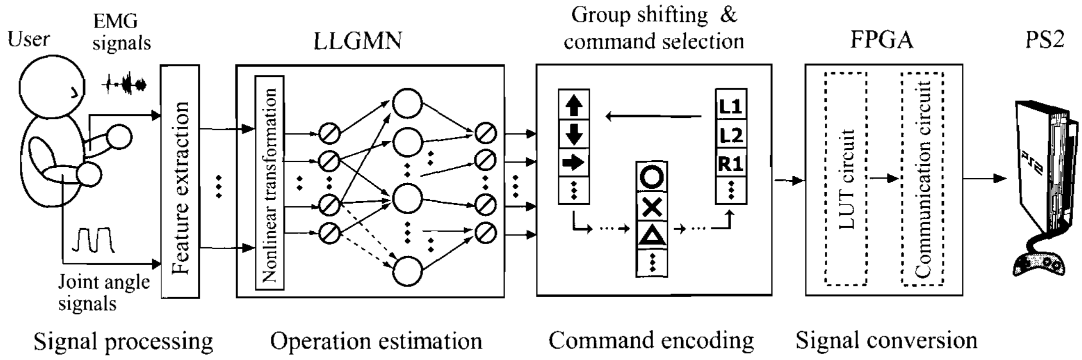


Fig. 2. Prototype of the proposed human interface for game control.

generation circuit uses a look-up table (LUT) to store the control signals in memory in advance, to match the selected commands to the address in memory, and to generate the required signal. When changing the game machine, simply rewriting to the LUT circuit memory creates an arbitrary control signal. By changing the communication circuit in-line with the required communication protocol, a single interface can control multiple game machines.

3. Prototype Development

The prototype we developed employs EMG signals and joint angle signals as input signal and PlayStation 2 (Sony Computer Entertainment Inc., PS2) for the operation (**Fig.2**). Ag/AgCl bioelectrodes (Yokogawa Electric Corporation) and small electromyograph (OE-BR-T-4001, Oisaka Development Ltd.) are used to measure the EMG signals, while shape sensor (S720, Measurand Inc.) measures the joint angle signals. The shape sensor consists of urethane-covered fiber-optic plastic, so when measuring, the bending direction of the sensor and its curvature are calculated by the amount of light lost from the sensor [13].

With the operation using EMG signals, feature extraction is performed in the input signal processor as follows. Full-wave rectification for EMG signals as measured by L-channels sensor and smoothed using a second low-pass filter whose cut off frequency is 2Hz, $EMG_l(t)$ $(l = 1, \ldots, L)$ is carried out. The normalized signals, which make the sum of all channels 1, are made into input vector $\boldsymbol{x}(t) = [x_1(t), x_2(t), \ldots, x_L(t)]^{\mathrm{T}}$ of time t, and are used for pattern recognition. Each vector element then becomes

$$x_l(t) = \frac{EMG_l(t) - EMG_l^{st}}{\sum_{l'=1}^{L}(EMG_{l'}(t) - EMG_{l'}^{st})} \quad \ldots\ldots (2)$$

where EMG_l^{st} is the average of the $EMG_l(t)$ measured at rest. The user's force information for input vector $\boldsymbol{x}(t)$ is defined as

$$F_{EMG}(t) = \frac{1}{L}\sum_{l=1}^{L}\frac{EMG_l(t) - EMG_l^{st}}{EMG_l^{max} - EMG_l^{st}} \quad \ldots\ldots (3)$$

where EMG_l^{max} is the average of $EMG_l(t)$ at maximum voluntary contraction of the muscle. By comparing $F_{EMG}(t)$ and threshold M_d of the movement occurrence decision, we can determine the timing of movement occurrence. When $F_{EMG}(t)$ exceeds M_d, movement is estimated from input vector $\boldsymbol{x}(t)$ using the PNN.

On the other hand, when using the joint angle signals, the signals are measured by the sensor, $SHP_l(t)$, and are normalized so the maximum of each channel is 1 and the minimum 0.

Each element of the vector becomes

$$x_l(t) = \frac{SHP_l(t) - SHP_l^{min}}{SHP_l^{max} - SHP_l^{min}} \quad \ldots\ldots (4)$$

where SHP_l^{max} and SHP_l^{min} are the maximum and minimum measured signals, respectively. Energy information for the joint angle signals is defined as

$$P_{SHP}(t) = \frac{1}{L}\left|x_l(t) - x_l^{st}\right| \quad \ldots\ldots (5)$$

where x_l^{st} is the average of the input vectors measured at rest. As for the EMG signals, when $P_{SHP}(t)$ exceeds M_d, movement has occurred and the PNN estimates the user's movement.

In intention estimation, the biological signal pattern is recognized by using a log-linearized gaussian mixture network (LLGMN) [11] proposed by Tsuji et al. as the PNN. This network includes a Gaussian mixture model, which is a type of statistical model, and posterior probability is estimated by learning. Through this learning ability, biological signals, such as EMG signals, are discriminated precisely [5].

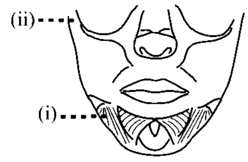
The entropy is calculated from the LLGMN output and discrimination is then determined [12]. Since the output $O_k(t)$ of the LLGMN represents posterior probability for each movement k $(k = 1, 2, \ldots, K)$, entropy is defined by the following equation, which shows the obscurity of information:

$$E(t) = -\sum_{k=1}^{K} O_k(t)\log O_k(t). \quad \ldots\ldots (6)$$

If $E(t)$ is smaller than discrimination determination threshold E_d, the movement with the highest posterior probability is the result of discrimination. Otherwise, if

$E(t)$ exceeds E_d, discrimination is suspended as obscure movement. To prevent incorrect movement, movement confirmation threshold O_{Th} is introduced. When a continuous discrimination number of discriminated movement k exceeds O_{Th}, k is confirmed as movement and the command is selected at the command decision.

The signal converter is designed using an evaluation board (Xtreme DSP Development Kit-II, Nallatech), on which the FPGA (XCV3000-4FG676, Xilinx Inc.) is mounted and the circuit is described using Verilog-HDL. The operating frequency is 2.5MHz, and the control signal bit width stored in memory is 16bits. The LUT and communication circuits are implemented based on the communication protocol of the PS2, which the user operates by using the EMG and joint angle signals.



(i) Depressor anguli oris
(ii) Zygomatic region

Fig. 3. Locations of sensors.

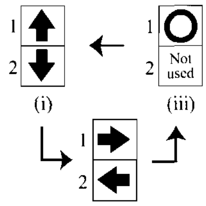
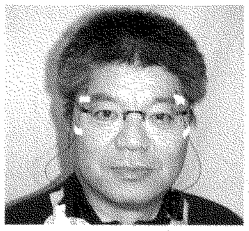
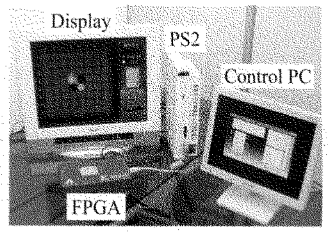


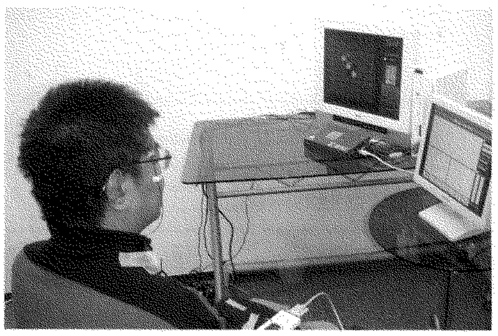
Fig. 4. Command groups.



(a) A patient with a cervical spine injury.



(b) Developed prototype system.



(c) An operation scene using the prototype system.

Fig. 5. Photos of the patient with cervical spine injury and the developed.

4. Experiments

4.1. Procedure

To verify the validity of the proposed interface, we conducted experiments using the prototype. Six subjects classified as A to F consented to the study. Subjects A and B are males aged 46 and 51 years old, respectively, who have cervical spine injury, whereas subjects C to F are healthy 22 year-old males. Subject A, who was injured at the fourth cervical spine, has function C4 and an ADL total assistance level caused by quadriplegia. Subject B, who was injured at the fifth cervical spine, has function C5, which is ADL total assistance level due to quadriplegia. Since subjects A and B could not move freely from the neck down, they could not operate the game via a conventional interface.

Because all subjects could maneuver the game, operation was conducted using biological signals measured from the sensors placed on the facial surface. We measured the EMG signals at the left and right depressor anguli oris muscles, whereas the joint angle signals were determined at the left and right zygomatic regions (**Fig.3**), and from two channel ($L = 2$) sensors.

The movements were right lateral muscle contraction, left lateral muscle contraction, and both lateral muscle contractions for the EMG signals. The three movements for the joint angle signals were right eye closure, left eye closure, and both eyes closure ($K = 3$). The sensor and movement were decided during the preparatory experiments conducted in advance, so subjects were able to operate the game easily, although they were modifiable based on the degree of disability. The game employed for the experiment was Othello (SUCCESS Corporation). There were 5 ($C = 5$) operation commands for Othello, i.e., they were the four directions of left, right, up, and down and a decision command for placing the stones.

For Eq.(1), the minimum number of groups was $G = 3$. Changing the group by commands, which are configured in each group, was decided based on **Fig.4**.

The experiment was conducted in an ordinary computer room at room temperature of about 20 to 25 deg Centigrade. Subjects A and B used electric wheelchairs. Subject A carried out the experiment wearing a respirator due to a tracheotomy. Consent of the subjects was obtained, who received detailed explanations of the purpose and content in advance. Each subject conducted the experiment after being trained several minutes prior to the start of the experiment.

For LLGMN learning, 20 sets of signals for each movement were randomly selected from the pretreatment for biological signals of each objective movement and subsequent feature extraction, for a total of 60 sets of patterns as teaching signals. The discrimination determination threshold was $E_d = 0.1$, which made manipulation easy for the subject in the preparatory experiment. For the decision for E_d, detailed investigations will be given in future studies.

Figure 5 shows **(a)** a subject suffering from a cervical spine injury wearing shape sensors, **(b)** prototype, and **(c)** operation scene using the prototype. Since the proposed system realized game operation through the generated biological signals of the user, severely handicapped people could benefit from the equipment.

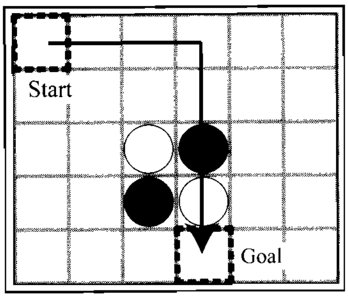


Fig. 6. Desired route and target position.

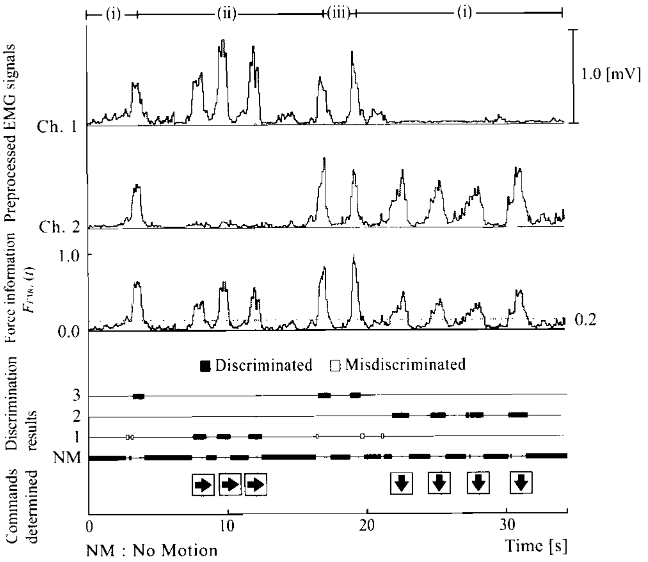


Fig. 7. Example of operations using EMG patterns (Subject A).

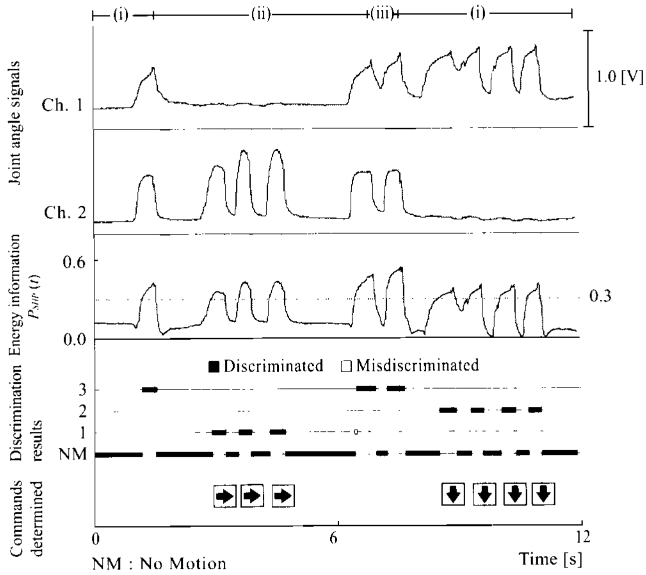


Fig. 8. Example of operations using joint angle patterns (Subject B).

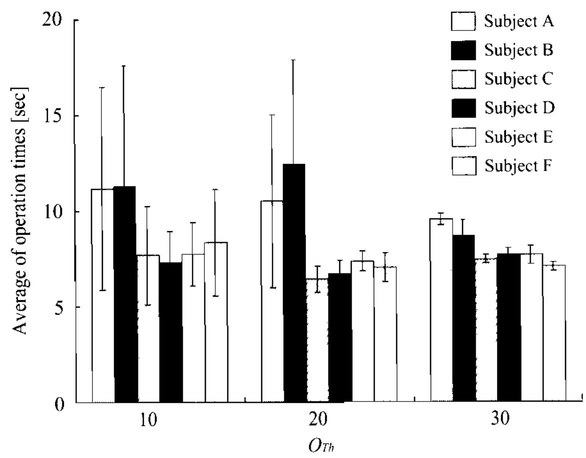


Fig. 9. Comparison of operation time for motion determination thresholds O_{Th}.

4.2. Operation Experiment

The experiment with the game was conducted by subject A, in which EMG signals were utilized. The instruction was given to move along the route as presented in **Fig.6**, and the threshold $M_d = 0.2$ of the movement occurrence decision and movement confirmation threshold $O_{Th} = 30$ were noted. An example of the result of the operation is shown in **Fig.7**. The figure shows, from top to bottom, a full-wave rectification, EMG signals after smoothing, force information $F_{EMG}(t)$, discrimination results, selected commands, and the performance of the game (shaded area). In discrimination results, an interval was defined as No Motion (NM) when no motion happened.

Although discrimination errors were confirmed, they were not judged as movements (refer to section 3) since the continuous discrimination number exceeded O_{Th}. The experiment confirmed that required commands were selectable by facial movement alone, and the game proceeded based on instructions.

An example of the experiment by subject B is shown in **Fig.8**. Subject B had strong paralysis on the left side, and since game operation was difficult with respect to contraction of the left depressor anguli oris muscle, the joint angle signals were used as input signal. The subject was told to move along the route in **Fig.6** and $M_d = 0.3$ and $O_{Th} = 30$ were noted. The figure shows, from top to bottom, joint angle signals, energy information $P_{SHP}(t)$, discrimination results, and selected commands. The figure confirmed that required commands were selectable by facial movement alone similar to the result drawn from the EMG signals. Therefore, when the biological signal changed based on the degree of disability through feature extraction on intention estimation and PNN, the game was done based on instructions.

The operation times are shown in **Fig.9**, when the movement confirmation threshold O_{Th} was changed. The vertical axis was the average of operation time for five trials. O_{Th} was set at 10, 20, and 30, and the route in **Fig.6** was instructed to six subjects. Subject B chose the joint angle signals for input while the other subjects selected

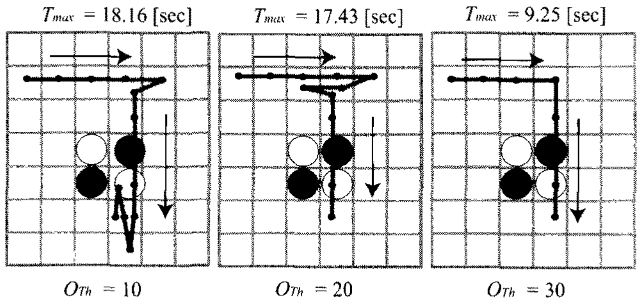


Fig. 10. Most time-consuming operations.

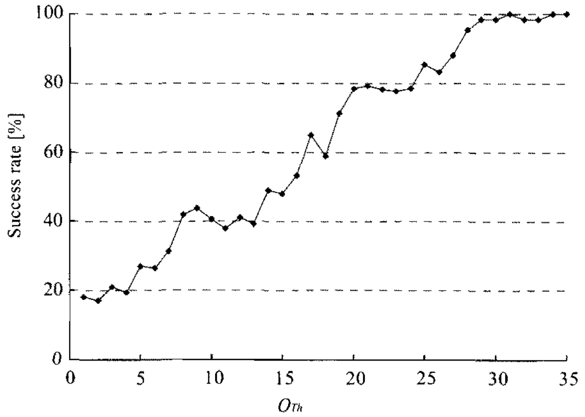


Fig. 11. Success rates for motion determination thresholds O_{Th} (Subject C).

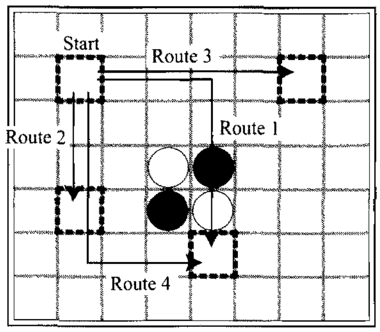


Fig. 12. Four desired routes used for evaluation of usability.

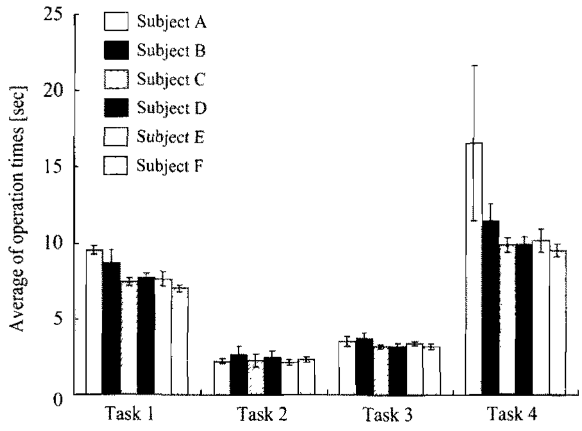


Fig. 13. Comparison of operation time in each task.

the EMG signals. In the experiment, the execution time was measured thus, each subject was instructed to finish as soon as possible.

We discovered the increase in variation in the operation time by reducing O_{Th}. For each O_{Th}, the most time-consuming trajectory of the trial operation is shown in **Fig.10**. We confirmed that when O_{Th} was small, operation on the instructed route became difficult and the number of overshoots rose. By making O_{Th} large, the operation was achieved based on the instruction. Furthermore, a stable operation time was obtained at $O_{Th} = 30$ for both non-handicapped and disabled people. By choosing the appropriate O_{Th}, stable operation with a small variation in operation times is possible.

By successively increasing O_{Th} from 1 to 35, we studied successful task performance. The result is shown in **Fig.11**, where the horizontal axis is O_{Th}, vertical axis is the average task success rate, and subject C.

Average task success rate I_{suc} represents the ratio of the number of input commands versus the number of commands required for the task, as defined by the following equation:

$$I_{suc} = \frac{N_R}{N_I} \quad \dots\dots\dots\dots\dots\dots (7)$$

where N_R corresponds to the number of commands required for the task and N_I to the number of commands that the subject actually input. For example, in moving along the route in **Fig.6**, the number of commands required for changing the group and the movement of the cursor, N_R is 10.

When O_{Th} was 1 to 10, the success rate was 20% to 40%, however, with increasing O_{Th}, the success rate rose to be approximately 100% at the vicinity of $O_{Th} = 30$. We thus confirmed that $O_{Th} = 30$ was desirable for the conduction of a stable task.

Four tasks (**Fig.12**) were instructed to each subject and the execution time of each task was measured. Tasks 1, 2, and 3 were movements of the cursor from the initial to final position based on a designated route, and task 4 was placing stones at moved positions. Each task was conducted 5 times and $O_{Th} = 30$ was determined.

The average operation time of each subject is shown in **Fig.13**. A small variation in the result of tasks 1, 2, and 3 was obtained resulting in a stable operation. For task 4, the variation by subject A was large because an input error occurred for the command in one of five trials and the operation time was longer. For the remaining four trials, operations were conducted as for the other subjects.

The task success ratio (Eq.(7)) of each subject is shown in **Table 1**. From the table, we confirmed that all subjects had high success ratio as a whole. As the number of commands required for the task and the distance moved increase, operation time for each subject became longer although the operation was conducted as instructed.

Table 1. Success rates in each task: mean values and standard deviations for 5 trials.

Sub.	Task 1	Task 2	Task 3	Task 4
A	98.6 ± 3.78	100.0 ± 0.0	100.0 ± 0.0	92.3 ± 14.52
B	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0	97.6 ± 6.30
C	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0	97.6 ± 6.30
D	94.8 ± 8.87	100.0 ± 0.0	100.0 ± 0.0	97.6 ± 6.30
E	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0	95.2 ± 8.13
F	98.6 ± 3.78	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0

Mean ± S. D. [%]

5. Conclusions

In this paper, we proposed a novel human interface using biological signals to enable the operation of game machines by the physically disabled. The input of the method is gathered from multiple signals which are biological signals the user voluntarily controls. Hence, many users can use the interface by appropriately selecting the input signal based on the degree of disability and so on.

At present, EMG, joint angle, and ACC signals are supported by the system. Through adaptive learning by the PNN, the change in measuring position of the biological signals and individual variation of the users do not bring any difficulties and user movement can be precisely estimated. By using the FPGA, which is a reconfigurable hardware, it is possible to add and alter the game machine.

With the EMG and joint angle signals as input signal, and the PS2 as the object of operation, the prototype was developed and experiments conducted. Experiments confirmed that subjects suffering from cervical spine injury could operate the game as instructed. We also demonstrated that by appropriately setting the movement confirmation threshold O_{Th}, a stable game operation could result with only a small variation in the operation time.

Nevertheless, problems can still happen when operating the game, such as the effect when changing the game and fatigue upon prolonged use of the interface.

In the future, we plan to study the performance of the interface for operation of the game with a bigger population of subjects. Since available biological signals are few, we also plan to increase the signals that can be employed for input. Moreover, in order to expand the number of games controlled by the interface, we will conduct further study on a reduced operation time and enhanced system operation speed.

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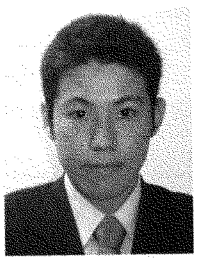

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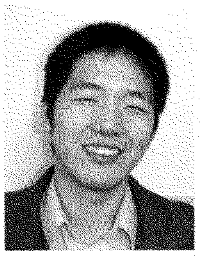

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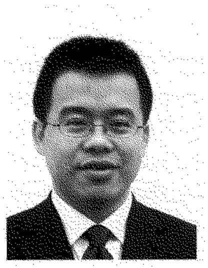

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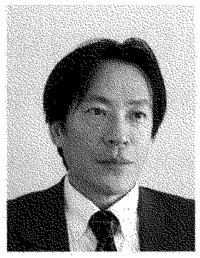

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